Using Neural Network for Urban Growth Modeling (Case Study: Gorgan City)

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Extended Abstract

Introduction

Artificial Neural network (ANN) models are knowledge-based models and fit within the regression type models of land use changes. ANNs are powerful tools that use a machine learning approach to quantify and model complex behavior and patterns. ANNs were developed to model the brain's interconnected system of neurons so that computers could be made to imitate the brain's ability to sort patterns and learn from trial and error, thus observing relationships in data.

Methodology

Land transformation model (LTM), of artificial neural network models, which couples geographic information systems with artificial neural networks, is used for urban growth modeling in Gorgan city between the years 1987-2001. This model consists of 6 applicable programs MS-DOS. The LTM follows four sequential steps: (1) processing/coding of data to create spatial layers of predictor variables; (2) applying spatial rules that relate predictor variables to land use transitions for each location in an area; the resultant layers contain input variable values in grid format; (3) integrating all input grids using one of three techniques; and (4) temporally scaling the amount of transitions in the study area in order to create a time series of possible future land uses. In Step 1, processing of spatial data, inputs are generated from a series of basic layers that are stored and managed within a GIS. These base layers represent land

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uses (such as agriculture and urban areas) or features in the landscape (e.g. roads, rivers, etc.). For Step 2, applying spatial transition rules, inputs are developed using a set of spatial transition rules that quantify the spatial effects that predictor cells have on land use transitions. The authors used three classes of transition rules: (1) neighborhoods; (2) distance from the location of a predictor cell; and (3) site specific characteristics. Step 3, integration of predictor variables, one of three different integration methods are used: multi-criteria evaluation (MCE), ANNs, and logistic regression (LR). Each integration procedure requires a different type of data normalization. We only present information relevant to the ANN integration method here. In Step 4, temporal indexing, the amount of land that is expected to transition to urban over a given time period is determined. The GIS portion of the LTM is encoded in Idrisi Kilimanjaro Software. ANNs are used to learn the patterns of development in the region and test the predictive capacity of the model, while GIS is used to develop the spatial, predictor drivers and perform spatial analysis on the results. In this research, three groups of variables including economic-social, land use and biophysical variables were used. 10 effective variables on urban growth (Slope, Distance to major roads, Distance to urban clusters in 1987, Distance to economic centers, Distance to medical centers, Distance to education centers, Number of urban cells within a 3×3 window, Bare land, Cropland/grassland, Forest, Cultivated land) are input nodes and dependent variable urban growth is output node. The use of hidden node is for identifying non-linear relationships.

Results and Discussion

Running model in 3000 th cycle had the least root mean squared error, and thus this cycle was used for extracting future urban growth and model sensitivity. To assess success of the modeling approaches, probability image of this cycle was used, and Relative Operating Characteristic value was calculated .075 that it result model validate. The ROC examines the agreement between a Boolean map of one category and a suitability map for that category. The ROC module offers a statistical analysis that answers to an important question: "How well is the category of interest concentrated at the locations of relatively high suitability for that category?" Using probability image, urban distribution patterns for 2010, 2020, 2030 and 2040 were created. Relative effects of the 10 predictor variables were evaluated through ROC, using 10 reduced-variable models and the full model. To do so, 11 different networks were created using the full and reduced-variable data set. The resultant network files were then used to create 11 different simulated images of urban change areas. Ranking and selecting the same number of pixels was done on each image to create the Boolean change image. The ROC was implemented using simulated and Boolean images. Using this method, the researchers found that removal of variables cultivated land and number of urban cells plus pasture land had the highest effect on ROC value and distance to education centers, forests and bare lands had the least impact on urban growth.

Conclusion

The kind (or type) of land use leads to a decisive effect on urban growth in the studied area. In many cases where there is a non-linear relationship between the dependent variable and independent ones, the neural network method normally produces results superior to other

methods. This method could also allow city managers to conduct an act play in the form of "What…. If?" scenarios and actually see the results of their decisions. This is of great importance as it can lead to setting aside of the plans that at the moment are thought to be useful but in the future produce more negative results.

Keywords: Artificial neural network, Urban growth modeling, Land transformation model, Roc, Gorgan city.